Benefits Transfer and Valuation Databases: Are We Heading in the Right Direction?

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The Incorporation of Prior Information and Expert Opinion in the Transfer Method: The Bayesian Approach

Presented by

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The Incorporation of Prior Information and Expert Opinion in the Transfer Method

Objective: The utilization of prior information for the transfer of benefits of environmental goods, with the transfer method.

The methods are Bayesian, i.e. they involve the utilization of Bayes' Theorem, although the elicitation methods can be applied without it.

The techniques involve the utilization of expert's opinion in benefit transfer, and how to elicit this opinion using statistical procedures.

Expert assessment was one of the earliest benefit transfer methods; what we show is how we can deal with it in a statistical setting.

QUESTIONS

1. Are we willing to complement the information of the study sites with some information from the policy sites? If the answer is yes, we could use a Bayesian approach to update the priors based on past information of the study sites.
2. How could we combine prior information from the pool of study sites with sample data? We present a model and results which were developed for this aim.
3. What impact could have prior information on predictions for the new policy site?

QUESTIONS

4. What methods can be used to elicit expert opinions and predictions about the value of a new environmental good or policy site?
5. How can the elicited experts' information be combined with sample observations on the new policy site?
6. How accurate are expert's predictions with respect to on-site observations on the policy site?
7. What could be the effect of new-site sample observations on expert's predictions?

Motivation

- Sample information could improve predictions for the new policy sites.
- Past information allows us to define a prior distribution of past study sites.
- All experts have prior beliefs about the future results.
- Prior beliefs can be based on the information from past studies and on prior experience.
- The elicited prior distribution could serve to form predictions on new policy site; and secondly it could be updated.
- From a theoretical point of view, the prior distribution might reflect the expectations from rational economic agents.
- However, predictions are not accurate under limited information, or when the model is not correctly specified.
- Expert opinion could provide adjustments to the new situations, based on previous knowledge and expertise on the underlying data development.

Outline

1. Bayesian methods and Benefit Transfer: The posterior and the predictive distributions.
2. Model for the pooling of prior information of study sites and its combination with sample information
3. Data description
4. Results on the model
5. Elicitation of expert opinion methods
6. Simulation methods
7. Results on elicitation
8. Concluding remarks

Bayesian Methods in BT

- In BT, Bayesian methods can be utilized as a general framework in which prior information can be handled to obtain predictions on the value of new environmental goods or policy sites. The application of a Bayesian approach requires the definition of a prior distribution. This can be obtained from expert opinion or from past studies.

- Expert opinion is very valuable when there is little information on the potential benefits of a particular policy site. Prior distributions can be elicited from experts using elicitation methods intended to derive the parameter of some specified model.

Bayesian Methods in BT

- Benefit transfer could be based on the elicited prior distribution, but the application of Bayes’ theorem allows the researcher to update the prior distribution by utilizing some sample data from the new policy site. Thus, in a Bayesian framework, benefit transfer can consider the role of sample information in complementing the lack of past information.

- Bayes' theorem (Bayes, 1763) involves the combination of prior information with sample information in order to derive a posterior distribution from which any inference can be made.

Bayesian Methods in BT

- Let us consider that the researcher is interested in estimating a parameter θ, which can be considered as the consumer surplus to be obtained from a new policy site, and can be a function of unknown parameters.

- If there is some knowledge on the possible values to be obtained in an empirical study, this information can be represented with the specification of a prior density distribution $\pi(\theta)$ which contains the probability of observing θ parameter before empirical data is collected, based on all available evidence from past experience. The prior distribution could also incorporate beliefs from expert opinion.

The Posterior Distribution

- If data is collected from the new policy site, this will be useful to define a likelihood function $f(x \mid \theta)$,which represents the likelihood of obtaining sample given that the population behaves according to parameter θ. This sample information allows the researcher to update her prior beliefs by applying Bayes' theorem. That is:

$$\pi(\theta \mid x) = \frac{\pi(\theta) f(x \mid \theta)}{\int_{\Theta} \pi(\theta) f(x \mid \theta) d\theta} \propto \pi(\theta) f(x \mid \theta)$$

- This is the expression for the posterior distribution, which is derived by combining the prior distribution and the likelihood function, and where $\propto$ denotes proportionality.

The Predictive Distribution

- In benefit transfer, it is most useful to consider the predictive distribution. This gives the probability of observing new sample data, given past experience and sample observations. That is,

$$m(y \mid x) = \int_{\Theta} f(y \mid \theta)\pi(\theta \mid x)\,d\theta$$

- where $f(y \mid \theta)$ is the likelihood for the sample observations which would be generated from a specific study for the new policy site, given parameter θ. This likelihood does not need to be the same as the one generating past observations.

Model for Pooling Prior Information

- Let us consider that the analyst has access at least to the mean consumer surplus from each study site in order to evaluate a pooled prior distribution. Each study site could be evaluated with a distribution represented by the mean. Let us assume a mixed distribution for the set of study sites, which is defined as a convex linear combination of prior distributions.

Thus, let $\pi\ (\lambda)$ be this joint distribution defined as:

$$\pi(\lambda) = \sum_{j=1}^{m} w_j \cdot \pi^j(\lambda)$$

Where λ is mean consumer surplus, m is the number of study sites, $\sum_{j=1}^{m} w_j = 1$, and $\pi^j(\lambda)$ is the prior distribution or density for each study site j. The weights w_j represent the similarity of study site j with the policy site. These weights do not need to be exogenously assessed by the decision-maker. They could be determined by analyzing the characteristics across the set of study sites, and using factorial design in order to allocate higher weights to the most similar sites. If there is only one study site which is relevant, for instance s, then $w_s = 1$.

The specification of the joint prior distribution requires the distribution for each of the study sites to be defined. Assuming a least informative distribution is a convenient way to model limited study site information based on mean consumer surplus.

Thus, let a maximum entropy distribution be considered (Jaynes, 1968), which is defined for each site *j* on the parameter of interest, i.e. consumer surplus λ_0^j. That is:

$$\pi^j(\lambda) = \frac{ke^{-k\lambda}}{\left(e^{-ka_j} - e^{-kb_j}\right)} \left(j = 1,\ldots,m\right)$$

where a_j and b_j are specified in the domain of each study site benefits, and parameter *k* is obtained by solving a non-linear equation

However, if the analyst has a clear belief about the shape of the distribution, represented by some parametric form, she could define a shifted Beta distribution such as

$$\pi^{j}(\lambda) = \frac{\Gamma(\alpha_j + \beta_j)}{\Gamma(\alpha_j)\Gamma(\beta_j)(b_j - a_j)^{\alpha_j + \beta_j - 1}} (\lambda - a_j)^{\alpha_j - 1} (b_j - \lambda)^{\beta_j - 1}, (j = 1, \ldots, m)$$

where *aj* and *bj* are specified in the domain of the benefits for each study site. This distribution is continuous and defined over an interval from *aj* to *bj.* The specification of the parameters leads to alternative families for the distribution.

For instance, the researcher could specify a Beta family with unimodal right skewness distributions. The expressions for the mean and mode are as follows:

$$Mean = a_j + (b_j - a_j)\frac{\alpha_j}{\alpha_j + \beta_j}$$

$$Mode = a_j + (b_j - a_j)\frac{\alpha_j - 1}{\alpha_j + \beta_j - 2}$$

Parameters α_j and β_j can be obtained by solving the latter two equations, and therefore determining the prior mean and mode for the informative distribution. When the practitioner has some knowledge of the potential range of the parameters, as well as of the feasible shape of the distribution, these quantities can be used to check the consistency of the prior distribution.

Now, suppose there is also some sample information from the policy site and the task is how to combine it with the joint prior distribution.

Assuming the sample elicitation process leads to *k* different consumer surplus values (i.e. willingness to pay) $V_0, V_1, \ldots, V_k$. Let P_i $(I = 0,\ldots,k)$ denote the population proportion for each of the observed values V_i $(I = 0,\ldots,K)$. Considering a random sample of size *n*, let n_i $(I = 0,\ldots,k)$ be the observed frequency for sample observation V_i $(I = 0,\ldots,k)$.

These sample data on the benefits of the policy site can be represented by a multinomial distribution as follows:

$$L(p_0,\ldots,p_k) = \frac{n!}{n_o! \ldots \cdot n_k!} \prod_{i=0}^{k} p_i^{n_i}$$

By Bayes' theorem, the posterior probability function can be calculated as:

$$\pi\left(\lambda \middle| data\right) = \sum_{j=1}^{m} w_j(data) \cdot \pi^j\left(\lambda \middle| data\right)$$

where

$$w_j(data) = \frac{w_j \cdot p(data|\pi^j)}{\sum_{k=1}^{m} w_k \cdot p\left(data \middle| \pi^k\right)} = \left\{1 + \frac{\sum_{k \neq j} w_k \cdot p\left(data \middle| \pi^k\right)}{w_j \cdot p(data|\pi^j)}\right\}^{-1}$$

and

$$p(data|\pi^j) = \int L\left(p_o, \ldots, p_k \middle| \lambda\right) \cdot \pi^j(\lambda) \cdot d\lambda$$

Is the predictive distribution of π^j for each study site j = 1,…,m.

Applications of Valuation Methods to Spanish Natural Areas 2001

Data - Study Sites

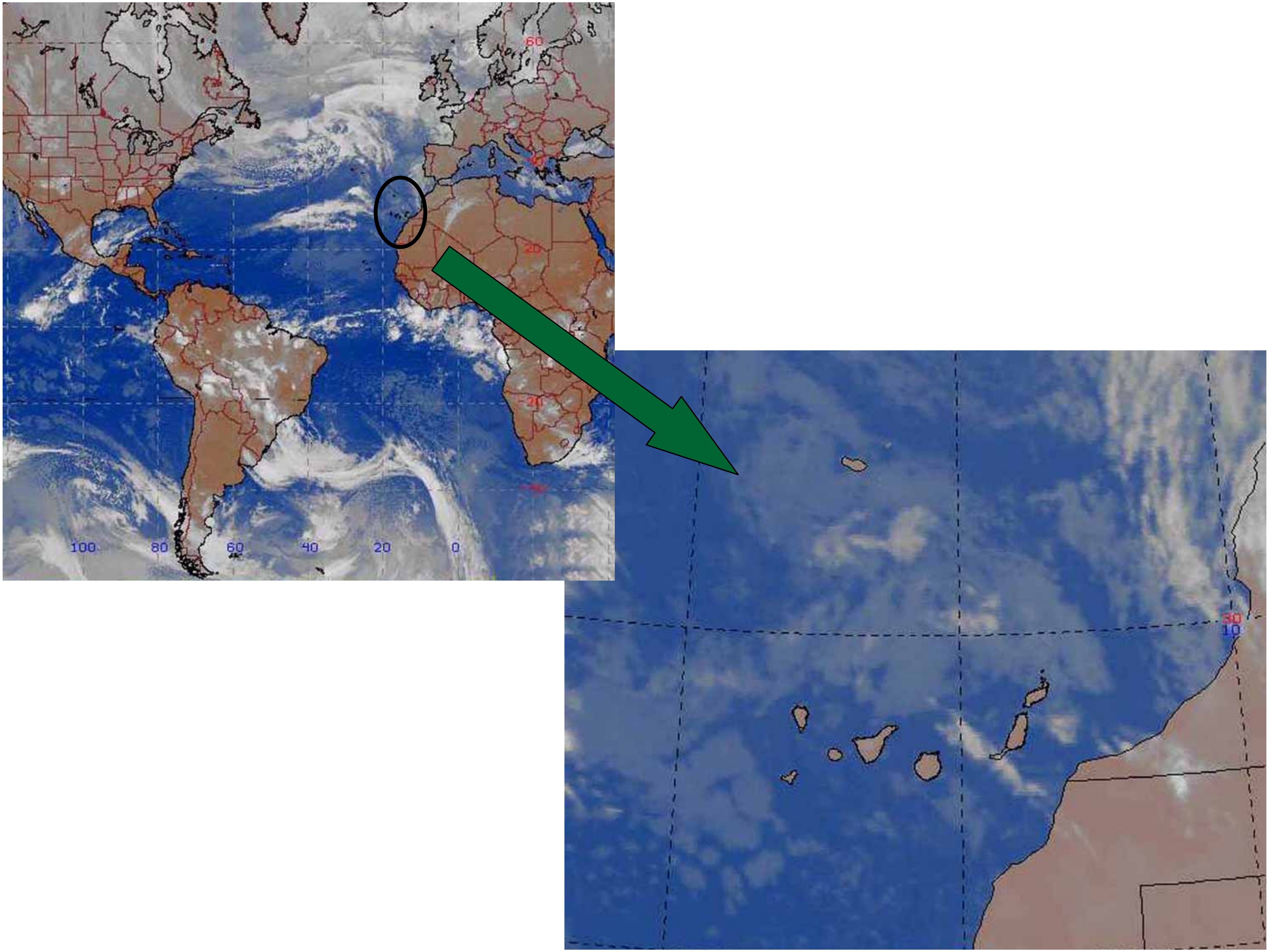
T-1. Selected CVM Applications to Spanish Parks

Year	Reference	Natural Space	Payment Method	Elicitation Format	Sample Size	WTP (ptas)
1993	Riera et al. (1994)	Plà de Boavi (Catalan Pyrenees)	EF	SB	300	1252
1994	León (1997)	Gran Canaria Natural Parks	EF	DB	573	1509
1994	Campos et al. (1996)	Monfragüe Natural Park (Extremadura)	EF	SB	420	1468
1995	Pérez et al. (1996)	Ordesa and Monte Perdido National Park (Pyrenees)	EF	SB	545	1203
1995	Del Saz (1996)	La Albufera Natural Park (Valencia)	EF	SB	501	623
1995	González (1997)	Monte Aloia Natural Park (Galicia)	EF	SB	402	403
1997	Júdez et al.(1998)	Tablas de Daimiel Natual Park (Castilla- La Mancha)	EF	SB	366	943

Spanish National Parks

1. Islas Atlánticas
2. Picos de Europa
3. Ordesa y Monte Perdido
4. Aigüestortes y lago Sant Maurici
5. Cabañeras
6. Tablas de Daimiel
7. Archipiélago de Cabrera
8. Doñana
9. Sierra Nevada
10. Caldera de Taburiente
11. Garajonay
12. Teide
13. Timanfaya

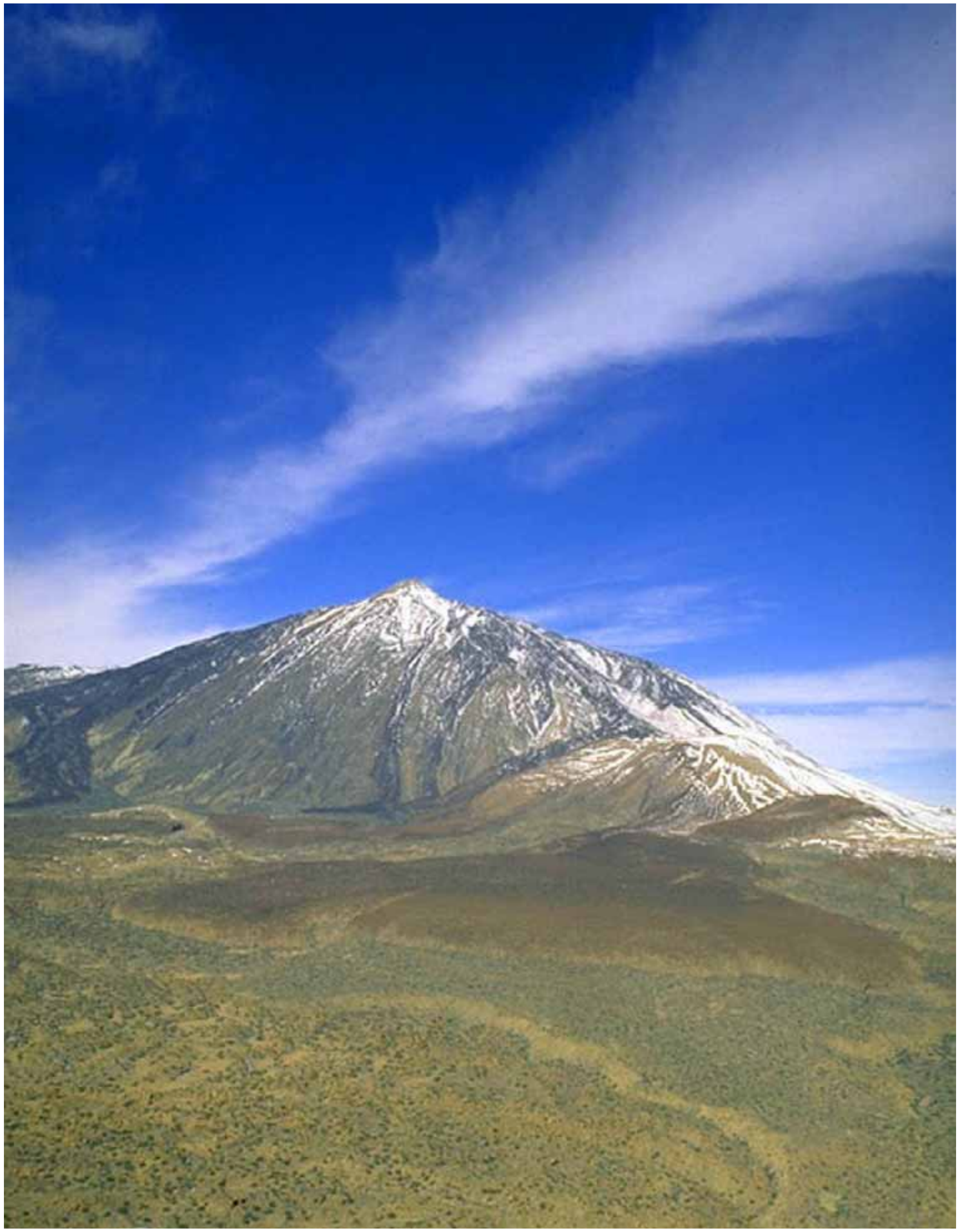
Spanish National Parks



100
80
60
40
20
0
30
10

Policy sites – Teide National Park

Teide National Park in Tenerife (Canary Islands), with15,000 hectares features endemic highland vegetation species as well as Mont Teide, a volcano which is the highest peak in Spain at 3714 mts. 3 million visitors per year.



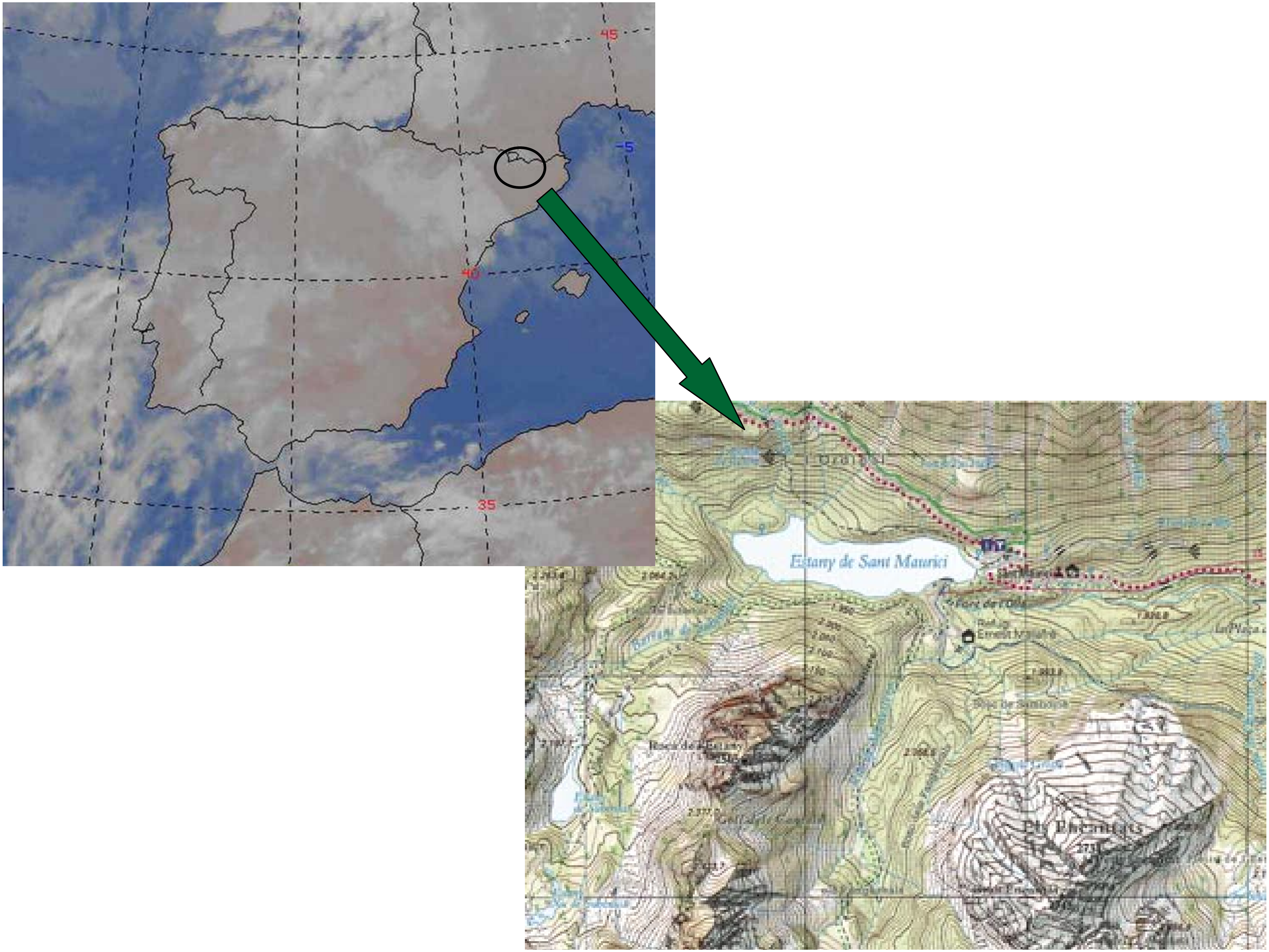
Teide National Park

- Flora is rich and singular, with species adapted to extreme climatic conditions, highlands, sun light and low humidity.
- Most species are endemic of the Cnary Islands, e.g. the violet of Teide.
- Endemic fauna is over 50%, and vertebrates are reptiles (lizards), bats and hedgehogs.

Taburiente National Park

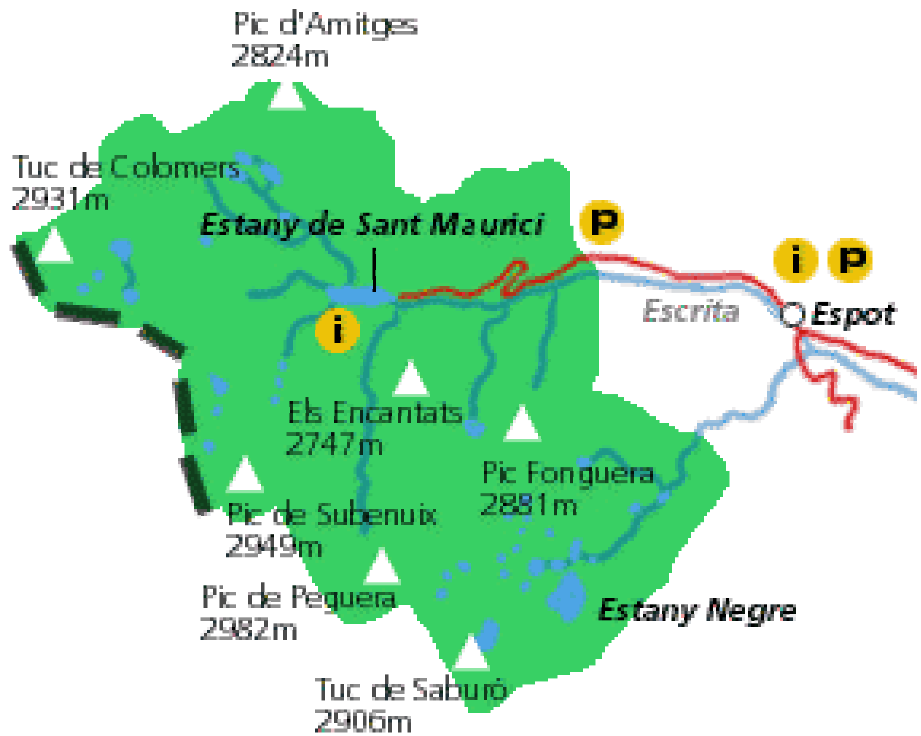
Taburiente National Park in La Palma (Canary Islands) features 4,690 hectares of endemic species of pine forests, and receives about 240,000 visits in a year.

It is formed by a large crater of 28 kms in the form a horseshoe, and with 2000 ms. high clifts, and many streams.


45
40
35
Estany de Sant Maurici

Aigüestortes i Estany de Sant Maurici National Park

The Aigüestortes i Estany de Sant Maurici National Park (Aigüestortes) is located in the Pyrenees, on the Catalan French border, near Andorra, with 14,119 hectares. The main attractions are the mountains and small lakes. 300,000 visits per year.



Aigüestortes i Estany

- 1.471 vegetal species, out of which 7,8% are endemic from the Pyrenees.

- 200 species of vertebrates, out of which a fourth are birds.

- There are also reptiles, butterflies, and insects.

Data - Policy sites

- Field work on study sites was conducted 1997 using CVM. After pre-testing and focus groups, samples were taken randomly in each of the parks, with 699 subjects in Taburiente, 1045 in Teide, and 643 in Aigüestortes, i.e. a total number of 2387 individuals.

- The questionnaires and the valuation scenarios were the same for all of the parks.

- The payment vehicle was a hypothetical entrance fee to the park.

- The valuation question focused on the enjoyment the park, incorporates a preservation motive for the reasons to pay, and remarked that all visitors would have to pay.

- The elicitation format was double bounded dichotomous choice based on a five bids vector design with open ended pre-test responses and the values of other natural areas.

RESULTS
T-2. Sample means for the National Parks

	Teide	Taburiente	Aigüestortes	Kruskall-Wallis test
AGE	37.36	37.68	36.54	4.33 (0.114)
FINC	7.49	7.43	7.20	2.39 (0.302)
PINC	5.19	5.32	4.95	4.69 (0.095)
YEDU	13.49	13.94	13.72	3.48 (0.175)
SEX	0.5	0.5	0.47	1.78 (0.409)
VISITS	1.72	1.78	1.75	4.76 (0.092)
BEFORE	0.16	0.20	0.15	9.40 (0.015)
GROUP	2.57	2.33	2.49	7.85 (0.019)

RESULTS
T-3. Generalized Gamma WTP Models

Parameters	Parks		
	Teide	Taburiente	Aigüestortes
Intercept	7.4900 (0.0435)	7.2671 (0.0638)	7.4269 (0.08511)
Scale	0.5816 (0.0262)	0.7731 (0.0371)	0.8511 (0.0550)
Shape	0.6734 (0.1415)	0.5938 (0.1576)	0.5512 (0.1983)
log L	-1026.29	-816.67	-668.73
n	845	609	525
Median (Pts.)	1561	1220	1430
Mean (Pts.) 95% C.I.	2081 (1870, 2234)	2028 (1805, 2323)	2700 (2462, 3138)

RESULTS

T- 4. Pooled Models

Parameters	Teide and Taburiente	Taburiente and Aigüestortes	Taburiente and Aigüestortes	Pooled
Intercept	7.4213 (0.0365)	7.4847 (0.0392)	7.3368 (0.0502)	7.4253 (0.0336)
Scale	0.6623 (0.0222)	0.6716 (0.0253)	0.5770 (0.1238)	0.7061 (0.0211)
Shape	0.6957 (0.1047)	0.6809 (0.1135)	0.5770 (0.1238)	0.6689 (0.0923)
n	1454	1370	1134	1979
log L	-1863.50	-1710.98	-1491.75	-2540.78
X^2	41.08	31.92	12.70	58.18

RESULTS

T- 5. Posterior mean and 90% credible interval from full sample (pts)

	Lower Bound		Weighted Average		Upper Bound	
Park	**MEP**	**Beta Prior**	**MEP**	**Beta Prior**	**MEP**	**Beta Prior**
Teide	1948 (1879, 2007)	1904 (1837, 1962)	1950 (1881, 2009)	1937 (1869, 1996)	1951 (1882, 2010)	1947 (1879, 2006)
Taburiente	1634 (1553, 1707)	1582 (1504, 1651)	1637 (1556, 1710)	1623 (1543, 1695)	1638 (1557, 1712)	1636 (1556, 1709)
Aigüestortes	1966 (1877, 2047)	1891 (1805, 1968)	1970 (1881, 2051)	1947 (1859, 2026)	1971 (1882, 2052)	1965 (1876, 2045)

RESULTS

T-6. Posterior mean and 90% credible interval from 10% sample (pts.)

	Lower Bound		Weighted Average		Upper Bound	
Park	**MEP**	**Beta Prior**	**MEP**	**Beta Prior**	**MEP**	**Beta Prior**
Teide	1915 (1710, 2116)	1579 (1410, 1742)	1939 (1732, 2141)	1821 (1630, 2007)	1945 (1738,2147)	1912 (1713, 2104)
Taburiente	1552 (1323, 1788)	1241 (1076, 1406)	1583 (1343, 1825)	1478 (1274, 1686)	1592 (1356, 1835)	1581 (1359, 1808)
Aigüestortes	1837 (1581, 2094)	1406 (1222, 1587)	1875 (1614, 2134)	1708 (1484, 1932)	1884 (1623, 2147)	1838 (1596, 2081)

Elicitation of expert opinion

- **Structural elicitation:** Experts are asked to assess directly the distribution of parameters, e.g. What would you think of the distribution of ß?
- **Predictive elicitation:** Experts are asked to make statements about predictive distributions of observable quantities, e.g. What is your median for the next observation?

a) **Deterministic phase:** Choice of functional form for model.

b) **Probabilistic phase:** The expert’s answer questions.

c) **Informational phase:** Answers are verified.

WTP Elicitation Method

The elicitation procedure starts by a number of questions that experts have to answer, based on their previous experience and information. Experts should be only asked to estimate the mean of a distribution and observable quantities, (Kadane and Wolfson, 1998). Thus, we consider the first moment and the quartiles of the distribution as the most relevant information to be obtained from experts.

ASSUMPTIONS

- Experts have an information set which is made of the results from all past studies on environmental valuation, and are familiar with basic concepts of statistics.
- Experts are asked to predict results according the specific model. The elicitation procedure is context specific, not only in terms of the definition of the good to be valued, but also in the methods to be used.
- Consider a contingent valuation model. The questionnaire would contain the elements of the non-market scenario, following standard protocols such as Arrow et al. (1993).

Elicitation model

The elicitation process has the object to elicit consumer surplus λ,and is carried out on the predictive distribution, which gives the probability of observing new sample data, given past experience and the results of previous studies, i.e.

$$m(y|x) = \int_{\Lambda} f(y|\lambda)\, \pi(\lambda|x)\, d\lambda,$$

where $f(y|\lambda)$ is the likelihood function for observations y to be obtained from a study conducted for the new policy site, given the expected parameter λ. x represents past data, and $\pi(\lambda|x)$ is the posterior distribution obtained from Bayes' theorem:

$$\pi(\lambda|x) \propto f(y|\lambda)\, \pi(\lambda).$$

i.e. the posterior distribution is the product of the prior distribution before any empirical data is observed $\pi(\lambda)$and the sample likelihood obtained from the data set available from previous studies $f(y|\lambda)\ \pi(\lambda)$.

Suppose to elicit the parameters of a shifted Beta density.

$$\pi(\lambda;\ \alpha,\beta,a,\ b) \propto (\lambda\text{-}a)^{\alpha-1}\ (b\text{-}\ \lambda)^{\beta-1}, \quad a< \lambda<b.$$

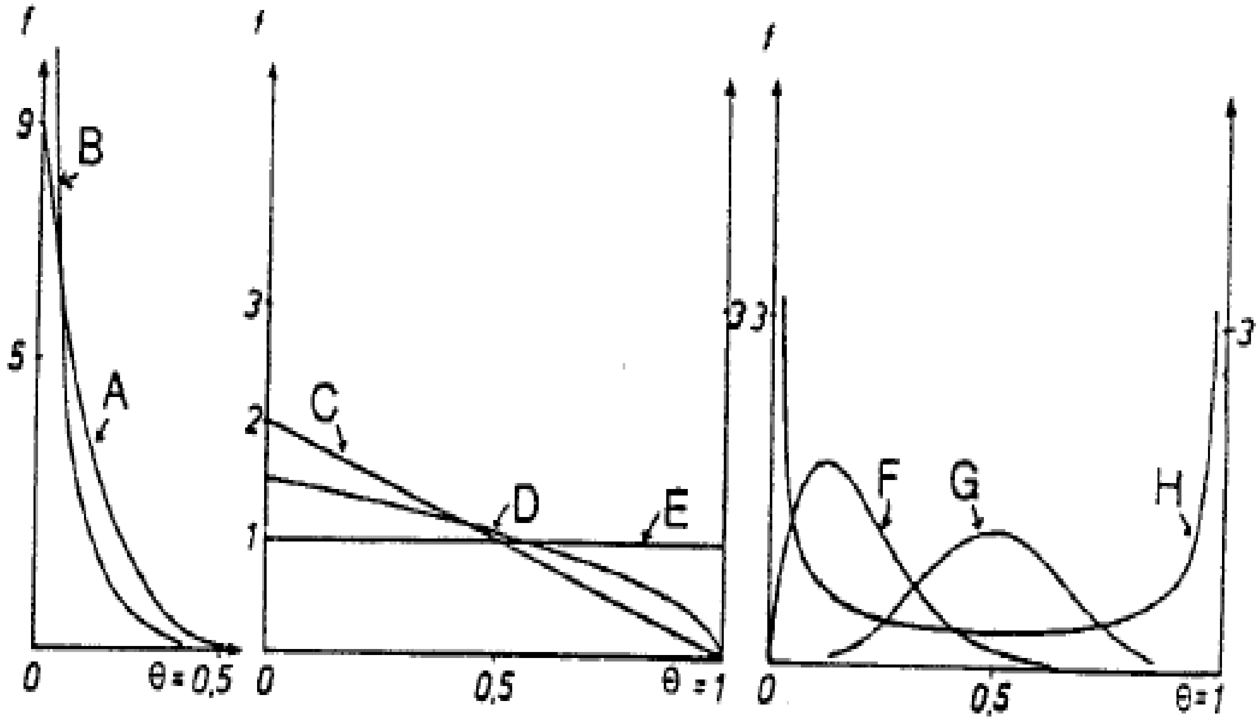
Where:

- a and b are the lower and upper bounds defining the range of WTP as determined by the expert.
- α and β are the parameters defining the quantities and the shape of the prior density.

Remarks:

- Shifted Beta distribution was chosen because its flexibility enhances interpretation by experts, allowing for a variety of shapes and skeweness.
- Contingent valuation data tend to be skewed, thus centered distributions such as normal and logistic, are not appropriate.
- Beta is rightward skewed if $1<\alpha<\beta$, and leftward skewed if $1<\beta< \alpha$.

The elicitation process could be most informative or less informative, depending on the amount of information which is asked from the expert.



Source: Hömberg, R. (1983)

LIM Method

Least Informative Method (LIM):

Step 1: Ask the expert for λ (mean) and d (mode) for the expected results to be obtained from the new policy site.

Step 2: Solve for parameters α and β, taking into account responses in Step 1, and considering these two equations:

$$\lambda = a + (b-a)\,(\alpha/(\alpha+\beta)),$$

$$d = a + (b-a)\,((\alpha-1)/(\alpha+\beta-2)),$$

Step 3: Present to the expert the results on the shape as elicited in Steps 1 and 2, asking for revision and adjustment.

Step 4: Repeat steps 1 to 3 until agreement is attained.

MIM Method

Most Informative Method (MIM):

Step 1: Ask the expert for λ (mean) and d (mode), and quartiles (q_1, q_2, q_3) to be expected from the policy site.

Step 2: Let $\alpha=\beta=1$ and check whether the closed interval defined by q_1 and q_3 comprises a 50% high density region for a distribution Beta(α,β).

Step 3: If condition in Step 2 is not satisfied, α is increased by 0.01 i.e. α+0.01, and the corresponding parameter β is generated by.

$$\beta = (\alpha-1)((b-a)/(d-a)) - \alpha+2.$$

This step is repeated until parameters α and β satisfy the following two equations:

$F(q_1; \alpha, \beta) = 0.5$, and $F(q_3; \alpha, \beta) = 0.75$

where F is the Beta cumulative function.

When convergence is achieved, interval $[q_{1,}\ q_3]$ defines a 50% high density region for the prior parameters (α^*, β^*).

Step 4: Consistency is checked by considering whether q_1 does satisfy $(q_1; \alpha^*, \beta^*) \approx 0.25$ and the prior mean

$$\lambda = \alpha^*/(\alpha^*,+\beta^*) .$$

Step 5: If the either the elicited first quartile or the mean deviate in more than 30% from those specified in step 1, then the expert is asked to reassess the elicited quantities, until consistency is achieved.

The Likelihood function

Let us assume a loglogistic distribution for WTP, i.e.

$$G(x) = \frac{(x \cdot \exp(-\delta))^{1/\sigma}}{1 + (x \cdot \exp(-\delta))^{1/\sigma}}$$

This implies that the logarithm of willingness to pay follows a logistic distribution with location and scale parameters δ and σ, respectively.

In the case of the double bounded format the likelihood for data is:

$$f(\tilde{x} \mid \delta, \sigma) = \prod_{i=1}^{n} (\pi_i^{yy})^{\nu_1 \nu_2} (\pi_i^{yn})^{\nu_1 (1-\nu_2)} (\pi_i^{ny})^{(1-\nu_1)\nu_2} (\pi_i^{nn})^{(1-\nu_1)(1-\nu_2)}$$

Where ν_1 takes the value one if the individual answered “yes” to the first question and zero otherwise, and ν_2 takes the same values but for the second question. The mean WTP can be expressed as:

$$\theta = \exp(\delta)\Gamma(1+\sigma)\Gamma(1-\sigma)$$

Simulation with MCMC

The posterior distribution which results from combining a shifted Beta prior with a loglogistic likelihood does not belong to any standard family of statistical distributions. We utilize Markov Chain Monte Carlo methods in order to evaluate the posterior distribution by simulation form a succession of random values.

After convergence is reached, the values in the succession, called Markov Chain, can be considered as approximate draws from the posterior distribution.

Elicitation of the prior distribution

EXPERIMENT WITH EXPERTS

- o Students were trained in CV models and were read on valuation experiences in Spain and other countries. Only 5 students passed the exam on statistics and on general knowledge on valuation to be experts for the experience.
- o They were informed about the Parks to be valued.
- o They were given the questionnaire for field work.
- o Assume double bounded dichotomous choice with a loglogistic distribution.
- o Assume all protest responses are excluded.

RESULTS

T-7. Expert assessment elicitation results (in pts.) for Teide National Park

Quantity	Expert					
	#1	#2	#3	#4	#5	Average
Mean	1775	3700	2500	1300	1200	2095
Mode	1000	2500	1000	800	900	1240
First Quartile	700	1300	700	300	600	720
Median	1200	2700	2200	1190	1000	1658
Third Quartile	1500	4300	3300	1350	1400	2370
Maximum WTP	3200	10000	7500	3000	1900	5120
α	2.1	1.54	1.13	3.98	0.42	2.76
β	3.42	2.62	1.85	6.96	0.36	6.51
Deviation %	30	0	10	20	10	30

RESULTS

T- 8. Expert assessment elicitation results (in Pts.) for Taburiente National Park

	Expert					
Quantity	#1	#2	#3	#4	#5	Average
Mean	800	3000	1800	950	1500	1610
Mode	600	2000	1250	600	900	1070
First Quartile	500	1500	960	250	700	782
Median	750	2500	1500	600	1200	1310
Third Quartile	1000	3500	1700	825	2000	1805
Maximum WTP	1600	5000	5000	2300	3000	3380
α	1.33	0.64	4.46	2.52	0.72	2.69
β	1.55	0.46	11.38	5.31	0.35	4.65
Deviation %	7.6	0	20	22	30	20

RESULTS

T-9. Maximum likelihood estimation
(s. d. and 95% confidence intervals in brackets)

Quantity	Teide	Taburiente
δ	7.33575 (0.02409)	7.08438 (0.03596)
σ	0.36088 (0.01525)	0.46531 (0.02256)
Median (Pts.)	1534 (1463, 1611)	1193 (1106, 1279)
Mean (Pts.)	1919 (1807, 2035)	1754 (1582, 1946)
log L	-1016.21	-813.34

RESULTS

T-10. Posterior results for Teide by expert's prior

Prior	μ	σ	Mean
Expert # 1	0.4270 (0.02375)	0.3612 (0.01515)	1920 (1831, 2024)
Expert # 2	0.4288 (0.02328)	0.3616 (0.01502)	1925 (1830, 2027)
Expert # 3	0.4280 (0.02338)	0.3616 (0.01502)	1926 (1832, 2034)
Expert # 4	0.4225 (0.02361)	0.3602 (0.01481)	1909 (1819, 2007)
Expert # 5	0.4136 (0.01504)	0.3568 (0.010904)	1883 (1835, 1899)

RESULTS

T-11. Posterior results for Taburiente by expert's prior

Prior	μ	σ	Mean
Expert # 1	0.1135 (0.03150)	0.4329 (0.01682)	1559 (1508, 1594)
Expert # 2	0.1803 (0.03618)	0.4656 (0.02238)	1767 (1647, 1937)
Expert # 3	0.1794 (0.035510)	0.4648 (0.02190)	1762 (1636, 1917)
Expert # 4	0.1625 (0.03310)	0.4569 (0.02021)	1708 (1636, 1917)
Expert # 5	0.1780 (0.03581)	0.4654 (0.02437)	1762 (1623, 1937)

CONCLUSIONS

1. Elicited prior distributions can be used to predict the values to be obtained in an empirical study.
2. On-site data could be useful for updating the prior distribution in the light of new evidence.
3. The influence of the prior diminishes as the sample size increases because of the information from the new site.
4. Experts assessment does not match the empirical result. A consensus promises to be more successful.
5. Experts performed better in predicting the relative values of the two parks considered in the study.

LINES OF FUTHER RESEARCH

a. Develop more intuitive elicitation methods.
b. Expand to elicit models with covariates.
c. Application to other models of non-market valuation.
d. Sensitivity to the market construct and/or the econometric techniques.
e. Sensitivity across environmental goods, particularly for those which are not well known and studied.

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The Incorporation of Prior Information and Expert Opinion in the Transfer Method: The Bayesian Approach

Presented by

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